Interim Employment and a Leading Indicator for the Belgian Labour Market

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ABSTRACT
This paper focuses on the construction of a leading indicator for the Belgian labour market based on labour market variables. It is shown that our employment indicator constructed from monthly data on interim work and business failures: (1) resembles quite well the cyclical pattern of observed employment in Belgium and predicts the official employment figures up to 14 months ahead; (2) performs not significantly better when product market variables are added; (3) is a better predictor of the cycles in the labour market compared to existing leading indicators for the product market. Furthermore, it was found that even more accurate forecasts of future employment could be derived if information on the past behaviour of total employment (captured by an autoregressive process) was added to our constructed leading indicator. But this last specification loses its leading character due to long publication delays for the employment data.

1. Introduction

Most macroeconomic variables exhibit a similar cyclical pattern, representing the fluctuations in the aggregate level of economic activity, known as the business cycle. Because of timing differences, publication delays and other problems, it is however difficult to get a clear picture of the current and future state of the cycle based on these individual series. Therefore, a number of leading economic series are combined into a composite leading indicator. So far, most national as well as international institutes constructed only leading indicators for the product market. The aim of this paper is to construct a leading indicator for the Belgian labour market. The main purpose of this indicator is to predict the cyclical pattern, as well as the timing of the turning points in the employ-

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ment series. This exercise is especially relevant for Belgium because this country lacks high-frequency (monthly or even quarterly) data on total employment. Furthermore, the yearly employment figures are published with an average lag of 12 months. As will be shown in this paper, it is possible to find some variables (quickly available at a monthly basis) which lead the actual pattern of total employment with at least 2 months, hence employment can be predicted minimum 14 months ahead.

The construction of our labour market indicator will be based on the standard OECD/NBER methodology of constructing composite leading indicators (OECD(1987), Nilsson (1987)). But in contrast with other applications, we will concentrate on the labour market and hence experiment with the construction of an employment indicator using only labour market variables\(^2\). Monthly figures on business failures and the total number of hours worked via interim contracts will prove to be very successful as leading variables for total employment. Especially interim employment seems to be very sensitive to changes in the economic climate due to the extreme flexibility in hiring and firing interim workers, hence it can be assigned a key role in predicting the cycles in the labour market. In case of a sudden increase in economic activity, firms often prefer to hire (initially) only interim workers, in particular when they are faced with high hiring and firing costs for regular workers\(^3\) and uncertainty about the size and persistence of the shocks. On the contrary, interim workers will be the first to be laid off in case of a downturn. The observation that interim contracts are more and more used as a flexible way to absorb cyclical shocks is confirmed by some recent surveys. According to a Sobemap survey conducted in 1996, 21\% of the firms indicate increased labour flexibility as an important motive to make use of interim work. Note that four years earlier, this motivation was only significant for 9\% of the firms, while traditional reasons (e.g. replacement of permanent staff) were still dominating.

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\(^2\) Because most shocks in the product market are propagated to the labour market, similar cycles can be expected. This, however, does not imply that product market variables are the most appropriate indicators for the labour market, because it is highly possible that the timing as well as the amplitude of the cyclical changes is very different.

\(^3\) According to several indices constructed to rank countries in terms of labour market strictness, Belgium always appears at the top of countries with the most strict employment protection (see among others Emerson (1988), Grubb and Wells (1993)), OECD (1994)).
The paper is organised as follows. After the selection of the reference series and the potentially leading variables, a short overview is given of the consecutive steps required in order to identify the cyclical component of each selected series. These steps imply the elimination of seasonal, irregular and trend components. The next section describes how several cyclical components are aggregated into a composite leading indicator and how this indicator can be evaluated. In an extension, it will be tested whether adding a simple autoregressive process to the leading indicator leads to any significant improvement in predicting the actual cycles in the labour market.

2. Constructing a leading indicator for the Belgian labour market

In this section a leading indicator for the Belgian labour market will be constructed by using labour market variables and following the OECD/NBER methodology (OECD(1987), Nilsson (1987)).

2.1. Selection of the series

Because we will construct a leading indicator for the Belgian labour market, total employment in Belgium is the obvious reference series. The Ministry of Employment and Labour (Ministerie van Tewerkstelling en Arbeid) publishes data on this variable, but the main problem is that this is done only on a yearly frequency and is based on an estimation of the total employed population on 1 day (30\textsuperscript{th} of June). The R.S.Z. (Rijksdienst voor Sociale Zekerheid), however, collects also quarterly data\textsuperscript{4}, but this covers only the employees in the private sector. Furthermore, this data is only available for the period 1993Q1-1997Q1 and published with a delay of 12 months.

The next step is to select economic variables whose cyclical movements typically predate those of the reference series. The top part of table A1 (see appendix) gives an overview of the variables which can be used to construct a leading

\textsuperscript{4} This data is also based on an estimation of the employment at four particular days (31/3, 30/6, 30/9 and 31/12), rather than calculations of the labour volume (i.e. number of employed persons multiplied by the actual hours worked per person).
labour market indicator. Data on all these variables is quickly available and appears on a monthly basis. Note that data on interim employment is collected separately for blue-collar and white-collar workers. The main motivation for this distinction is that Belgian figures show that blue-collar interim employment reacts more sensitive to business cycle fluctuations, compared to the volume of white-collar interim work. An important explanation can be found in the sectoral decomposition of the two types of interim work. In particular the industrial sector seems to make heavily use of interim work, mainly blue-collar workers, in order to cope with temporary increases in the workload. But because this sector is very sensitive to the general economic climate, blue-collar interim work follows quite closely the movements in the industrial production. Note that at the moment, blue-collar workers seem to dominate interim work in Belgium (63.2%), while the share of white-collar workers is only 36.8%\(^5\).

2.2. Identification of the cyclical components of the series

In order to identify the cyclical component of the selected series, we need to decompose\(^6\) each series into a seasonal, trend, cyclical and irregular factor. These four components are in fact determined by the method of decomposition used because they are not observable in reality. In our application it is assumed that the different components of all series are related in a multiplicative way, hence the underlying model can be written as: \( X_t = TC_t \times S_t \times I_t \) where \( X_t \) is the original (observed) series; \( TC_t \), \( S_t \), and \( I_t \) are respectively the trend-cycle, seasonal and irregular component.

The seasonal component is filtered out with the Census X-11 procedure developed by the US Bureau of the Census. The main motivation for choosing this technique is that it is easily applicable on a large scale and does not require a large number of observations\(^7\).

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\(^5\) This was however not the case in the beginning of the 1980's. At that time, both types of workers were nearly equally important, i.e. the share of blue-collar and white-collar workers was respectively 53.9% and 46.1% in 1982.

\(^6\) A classic, but debatable, assumption is that it is possible to decompose each series into these four components and that these factors are independent of each other.

\(^7\) Note that it was not possible to use any model-based technique for seasonal adjustment due to the small number of observations available for our data series.
This same technique is also used to derive the irregular components. Figure A1 (see appendix) visualises the decomposition of one series, namely TOT (i.e. the total number of hours worked during 1 month by white and blue-collar interim workers) into three components: the seasonal, irregular and trend-cycle component.

The next step is to extract the trend from the trend-cycle component. In our application, this was done via the Hodrick-Prescott (HP) method mainly because the rather short sample periods required a technique which can be applied on all the observations of the series. The smoothing parameter\(^8\) \(\lambda\) was set equal to the benchmark value of 14400, which is the recommended value for monthly data by Hodrick and Prescott. As is obvious from figure A2 (see appendix), this results in a non-linear trend (TOTT) which moves smoothly over time. In order to test the sensitivity of our results with respect to the value of the smoothing parameter, we have been experimenting with alternative values for \(\lambda\).

As you notice from figure A2, setting \(\lambda=1000000\) results in an approximation to a linear trend, while \(\lambda=100\) leads to a very flexible trend because the penalty for fluctuations in the trend is relatively low in this last case. Hence, different values of \(\lambda\) can affect the estimated trend. It is however important to mention that (as will be shown below) alternative values of \(\lambda\) do not affect the timing of the turning points. Hence, applying the HP-filter with the same benchmark value (\(\lambda=14400\)) to all series is justified given our research purposes of building a composite leading indicator.

The above described analysis yields estimates for the seasonal, irregular and trend component of each series. Hence, we are now able to derive the cyclical components\(^9\).

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\(^8\) Suppose we observe the values \(X_t\) through \(X_n\) and want to decompose the series into a trend \((T_t)\) and a stationary component \((X_t-T_t)\). The HP-filter determines the trend component series \([T_t]\) by minimizing the following sum of squares:
\[
\frac{1}{S} \sum_{t=1}^{S} (X_t - T_t)^2 + \frac{\lambda}{S} \sum_{t=1}^{S-1} [(T_{t+1} - T_t) - (T_t - T_{t-1})]^2
\]

The parameter \(\lambda\) is an arbitrary constant \((\lambda>0)\), reflecting the penalty for fluctuations in the trend series. The larger the value of \(\lambda\), the larger this penalty; hence the smoother the path of the estimated trend.

\(^9\) The cycle is calculated by elimination of the seasonal, irregular and trend component and is expressed as deviation from the trend ("deviation-cycles").
Note that we assumed a multiplicative relationship between the trend and the cycle for all variables. The cyclical component can then be calculated by dividing the trend-cycle component by the estimated trend and multiplying this result by 100. Figure A3 (see appendix) presents the cyclical component of the TOT-series, labelled as TOTC, derived after HP-detrending at the benchmark value for $\lambda$ ($\lambda = 14400$). In addition, this graph depicts the cyclical components derived for alternative values of $\lambda$, i.e. TOTC2 is based on TOTT2 ($\lambda = 1000000$) and TOTC3 on TOTT3 ($\lambda = 100$).

Note that the larger the value for $\lambda$, the smoother the estimated trend, hence the larger the cyclical fluctuations\(^{10}\). This should however not cause any problems in our application because all series will be detrended with the same value for $\lambda$ and all variances will be normalised in one of the following steps. Furthermore, the timing of the turning points, which is crucial when we aim to build a composite leading indicator, is not affected by the choice of $\lambda$. Hence, we will continue only with the series detrended on the basis of the benchmark value for the smoothing parameter ($\lambda = 14400$).

2.3. Composite indicator for predicting employment

Combining the cyclical components of several individual series to a composite indicator requires a number of steps.

At first, the different series have to be normalised so that the cyclical patterns have the same mean and standard deviation\(^{11}\). Otherwise, it is possible that indicators with strong cyclical fluctuations would dominate the cyclical pattern of the composite indicator.

Normalisation\(^{12}\) is done according to the following formula:

$$\left(\frac{(C - \mu_c)}{\sigma_c}\right) + 100$$

\(^{10}\) The standard deviations are respectively equal to 6.033 (for TOTC), 8.783 (for TOTC2) and 1.265 (for TOTC3). Note however that the higher moments are quite robust to the value of $\lambda$ (as shown by Canova (1998)), i.e. the skewness varies between -0.062 and 0.786 and the kurtosis between 3.010 and 4.796.

\(^{11}\) Normalising means is not necessary if the cycles are expressed as deviations from the mean. Furthermore, one should not normalize the amplitudes if these differences are taken into account when determining weights for the composite indicator.

\(^{12}\) Normalised series have an "N" in front of their name (e.g. NTOTC).
where C is the cyclical component and $\mu_C$ and $\sigma_C$ respectively its mean and its standard deviation. As a result, all cyclical series have mean 100 and unit standard deviation.

The second step consists of synchronising the different indicators. This is important in order to ensure that, on average, the turning points coincide and to ensure the reconstruction of the "appropriate" time-pattern of the business cycle. Usually, turning points of the cyclical component of the reference series determine the dating of the turning points of the business cycle. Therefore, leading series are lagged, while lagging series will be brought forward\textsuperscript{13}. The leading character of a series is not only determined on the basis of this turning point analysis, but also by maximizing the correlation between the indicators and the reference series. In our application, it is quite difficult to synchronise the different cyclical indicators, because we lack a good reference series for the labour market due to the non-existence of monthly employment series in Belgium. In order to get some idea of the cyclical pattern of total employment, the quarterly data on the normalised cyclical component of the EMPL-series (referred to as NEMPLC) has been converted – via linear interpolation- to monthly frequency. All normalised cyclical indicators are then changed in time (lagged or leaded) in order to maximise the correlation with NEMPLC and synchronise the turning points. Table A2 (see appendix) gives an overview of these correlation coefficients.

We now come to the final step in the analysis, namely the aggregation of several (normalised and synchronised) cyclical components into a composite leading indicator. Before doing so, we want to find out whether interim employment on its own is a good indicator of the future evolution of total employment. Figure 1 below visualises the cyclical pattern of the total number of hours worked during 1 month by white and blue-collar interim workers (NWHITEC and NBLUEC) and the reference series (NEMPLC). From this, it is very clear that interim employment is leading the actual employment series; more specifically we can say that NWHITEC and NBLUEC are leading NEMPLC with respectively 2 and 9 months\textsuperscript{14}. Given the publication lag of 12 months for the employment series, interim employment can predict 14 to 21 months ahead. Note that

\textsuperscript{13} Usually only leading series are used for constructing a composite indicator.
\textsuperscript{14} At these lags the correlation with the reference series is maximised (see table A2) and the turning points are synchronised.
the 7-months difference in the lagstructure between the two types of interim employment is not really surprising given the fact that blue-collar workers are mainly employed in the industrial sector. Because this sector is very sensitive to the economic climate, it is expected that fluctuations in the volume of interim work are first noticed in the segment of blue-collar work. Because white-collar work is less closely related to the industrial production, we expect that the movements in this type of work occur later in time.

FIGURE 1

The normalised cyclical component of BLUE, WHITE and EMPL.

Another main advantage of using NBLUEC or NWHITEC as a predictor of NEMPLC is that data on only 1 variable has to be collected. But it is also important to test the predictive performance of these two series and to analyse whether the addition of other variables can lead to more accurate predictions of total employment. The evaluation of the accuracy of forecasting will be based on four test statistics (namely the mean absolute error (MAE), the mean-squared

\[ U = \frac{1}{n} \sum_{i} (y_i - \hat{y}_i)^2 \]

\[ MAE = \frac{1}{n} \sum_{i} |y_i - \hat{y}_i| \]

\[ MSE = \frac{1}{n} \sum_{i} (y_i - \hat{y}_i)^2 \]

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i} (y_i - \hat{y}_i)^2} \]

where \( y_i \), \( \hat{y}_i \) and \( n \) are respectively the actual value, the predicted or forecast value and the number of observations.

\[ 15 \text{ These test statistics are defined as follows:} \]

error (MSE), the root mean-squared error (RMSE) and the Theil U-statistic (U)\textsuperscript{15}, regression analysis\textsuperscript{16} and plots of the actual versus the fitted values.

**TABLE 1**

Results measuring the accuracy of forecasting NEMPLC\textsuperscript{17}

<table>
<thead>
<tr>
<th>Test statistics</th>
<th>MAE</th>
<th>MSE</th>
<th>RMSE</th>
<th>U</th>
<th>α</th>
<th>β</th>
<th>adj. R\textsuperscript{2}</th>
</tr>
</thead>
<tbody>
<tr>
<td>NBLUEC(-9)</td>
<td>0.347</td>
<td>0.406</td>
<td>0.637</td>
<td>0.0064</td>
<td>21.468</td>
<td>0.786*</td>
<td>0.641</td>
</tr>
<tr>
<td></td>
<td>(15.544)</td>
<td>(0.156)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NWHITEC(-2)</td>
<td>0.483</td>
<td>0.440</td>
<td>0.663</td>
<td>0.0066</td>
<td>10.280</td>
<td>0.900*</td>
<td>0.669</td>
</tr>
<tr>
<td></td>
<td>(13.678)</td>
<td>(0.138)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMPLINDIC1</td>
<td>0.341</td>
<td>0.296</td>
<td>0.544</td>
<td>0.0054</td>
<td>-7.630</td>
<td>1.879*</td>
<td>0.757</td>
</tr>
<tr>
<td></td>
<td>(15.029)</td>
<td>(0.152)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMPLINDIC2</td>
<td>0.301</td>
<td>0.230</td>
<td>0.430</td>
<td>0.0050</td>
<td>-4.010</td>
<td>1.043*</td>
<td>0.802</td>
</tr>
<tr>
<td></td>
<td>(14.406)</td>
<td>(0.145)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As shown in table 1, these test statistics do not differ significantly between both interim series. But in contrast, two other evaluation criteria show a better performance of NWHITEC(-2), compared to NBLUEC(-9). On the one hand, the β-coefficient from the regression results is much closer to 1, while panel 1 and 2 in figure A4 (see appendix) indicate that NWHITEC(-2) does much better in predicting the exact timing of the turning points. So although changes in the economic environment are first noticed in the segment of blue-collar interim work, we opted to continue only with white-collar interim employment because this latter type provides better predictions of the cyclical pattern as well as the timing of the turning points in the total Belgian employment\textsuperscript{18}.

Because the NWHITEC-series only reflects cyclical movements in the temporary labour market (for white-collar jobs), we will now add a variable which

\textsuperscript{16} Because all variables have been detrended, we regress the actual value (here NEMPLC) on the predicted values, hence $y = \alpha + \beta \hat{y}$. A predictor is unbiased if the estimate of $\beta$ does not differ significantly from 1, while the estimate for $\alpha$ is not significantly different from 0. In case $\beta=1$ but $\alpha \neq 0$, we have a systematic (positive or negative) bias in the prediction, but this bias is independent of the predicted values.

\textsuperscript{17} The standard errors in brackets refer to the Newey-West heteroskedasticity and autocorrelation consistent standard errors and the coefficient estimates for $\beta$ indicated with * are not significantly different from 1 at 5% significance level.

\textsuperscript{18} From our analysis it is found that blue-collar interim work reacts first to economic shocks, but these movements are often more volatile than the actual movements observed in the total Belgian employment.
is explicitly related to the destruction of permanent employment, namely the total number of business failures (NFAILC)\textsuperscript{19}. Hence, we propose the following composite indicator for predicting total employment in Belgium\textsuperscript{20}:

\[ \text{EMPLINDIC1} = \frac{(NWHITEC(-2) + iFAILC(-10))}{2} \]

As can be seen from table 1, this composite indicator gives more accurate forecasts of NEMPLC. Furthermore, figure A4 illustrates that the addition of this variable reduces the forecasting errors and improves significantly the prediction of the turning points in the reference series. Hence, the benefits of this composite indicator exceed the associated costs of collecting data on one more series and aggregating two variables which are quite highly correlated with each other\textsuperscript{21}. In contrast, adding information on monthly vacancies (VAC1 or VAC2: definition see appendix table A1) did not lead to a further improvement in the forecasting performance of the employment indicator.

Note that the aggregation in the above described employment indicator is done by giving equal weights to the different components. Alternatively, one can use an unequal-weighted system, where the weights can for example be determined via correlation or principal component\textsuperscript{22} analysis. We have been experimenting with the latter technique on the two series used in the above specified employment indicator, namely NWHITEC and iFAILC (results not shown here). But because the coefficients for the first principal component\textsuperscript{23} showed

\textsuperscript{19} In contrast with other countries (e.g. the Netherlands), Belgium does not have official statistics on the number of layoffs because dismissals do not have to be approved by or reported to a government administration.

\textsuperscript{20} Because business failures are inversely related to employment, we take the inverse of the normalised cyclical component of the FAIL-series (called "iFAILC") when constructing a leading indicator for employment.

\textsuperscript{21} The correlation coefficient between NWHITEC(-2) and iFAILC(-10) equals 0.779.

\textsuperscript{22} Principal component analysis (see Jolliffe (1986) and Berk and Bikker (1995)) summarizes high dimensional data into a few dimensions. Each dimension is called a principal component and represents a linear combination of the variables. Principal components can be computed from the correlation or the covariance matrix. The first principal component is the linear combination of the variables that accounts for the greatest possible variance. In our application, this component can be interpreted as the business cycle. In order to get appropriate weights for a composite indicator, the coefficients of the first principal component have to be divided by the standard deviations of the associated series and rescaled to ensure that the sum of the weights equals 1. Hence, the weight derived for each individual series will be proportional to the correlation with the business cycle (as defined by the first principal component) and inversely correlated to its amplitude.

\textsuperscript{23} Note that the first principal component accounted for approximately 90% of the total variance.
that both series are about equally weighted, there is no purpose to use an unequal-weighted system\textsuperscript{24}.

In order to make the link between the product and labour market more explicit, we will now add a product market variable, namely NSALESC (at its optimal lag with the reference series), to the above described employment indicator. This results in the following alternative specification:

\[
\text{EMPLINDIC2} = (\text{NWHITEC(-2)} + \text{iNFAILC(-10)} + \text{NSALESC(-9)}) / 3
\]

Table 1 above indicates that this specification leads to more accurate forecasts of total employment, but note that these results are not significantly different from EMPLINDIC1. Furthermore, panel 4 in figure A4 (see appendix) shows that EMPLINDIC2 does worse in predicting the timing of the turning points in the reference series. Hence, the addition of the product market variable does not lead to a better leading indicator for total employment\textsuperscript{25}. This seems to suggest that either spillovers from the product to the labour market are insignificant or more plausibly- that our selected labour market variables (i.e. interim employment and business failures) are sufficiently able to capture these spillovers.

From the above described analysis we can conclude that although interim employment gives a clear indication of the cycles in the reference series, more accurate forecasts of the future levels of, as well as the turning points in, total Belgian employment can be derived by a composite indicator (EMPLINDIC1) constructed on the basis of white-collar interim work and the number of business failures.

A final test for our constructed employment indicator is to compare its performance with the performance of the existing leading indicators. Before proceeding with this comparison, we need to introduce four new variables. KBINDIC is the leading indicator for the product market developed by the Kredietbank\textsuperscript{26}. INDIC1 and INDIC2 are two synthetic indicators of the National Bank of Belgium (NBB), related respectively to the total economy and the manufacturing

\textsuperscript{24} In addition, we used OLS-regression coefficients as weights. This resulted in an alternative leading indicator which performed not significantly better than EMPLINDIC1.

\textsuperscript{25} Similar results were obtained with other product market variables (e.g. industrial production).

\textsuperscript{26} An elaborate description of the KB-indicator can be found in KB (1997).
sector only. From the monthly firm survey of the NBB it is also possible to get data on the expected employment evolution in the manufacturing sector for the following 3-months period (PREDEEMPL). All four series are then normalised as explained before and this results in the series NKBINDIC, NINDIC1, NINDIC2 and NPREDEEMPL.

Table 2 below presents the test statistics and regression results measuring the accuracy of forecasting NEMPLC via these existing leading indicators and compares them with those derived for EMPLINDIC1.

**TABLE 2**

Results measuring the accuracy of forecasting NEMPLC by existing indicators

<table>
<thead>
<tr>
<th></th>
<th>Test statistics</th>
<th>Regression results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>MSE</td>
</tr>
<tr>
<td>NKBINDIC(-6)</td>
<td>0.360</td>
<td>1.166</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NINDIC1(-10)</td>
<td>0.690</td>
<td>1.055</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NINDIC2(-10)</td>
<td>0.772</td>
<td>1.112</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPREDEEMPL(-8)</td>
<td>0.680</td>
<td>1.163</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMPLINDIC1</td>
<td>0.341</td>
<td>0.296</td>
</tr>
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<td></td>
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</tbody>
</table>

From this table, it is very clear that all existing leading indicators give significant less accurate forecasts of NEMPLC (i.e. higher values for the test statistics, lower values for $R^2$ and β-coefficients less close to 1), compared to EMPLINDIC1. Furthermore, table A2 (see appendix) indicates lower correlation coefficients between these indicators and the reference series, compared to our constructed employment indicator. And finally, plots of the actual versus the fitted values (see panel 5 and 6 in figure A4) show that these existing leading indicators are not able to give precise predictions of the turning points in NEMPLC. Hence, this proves the value-added of our leading indicator.

Note that this is not really surprising given the fact that these existing leading indicators (except NPREDEEMPL) were constructed with the purpose to predict the cyclical movements in the product market. In contrast, NPREDEEMPL is explicitly related to the labour market because it refers to the expected employment evolution in the manufacturing sector. But as is obvious from the comparison in table 2, this indicator based on qualitative information of a business survey does not perform well in predicting the cycles in the total Belgian employment.
(EMPLINDIC1) designed especially to predict the cyclical pattern of employment in Belgium.

2.4. Extension: adding an autoregressive process for employment to the constructed employment indicator

In this section we will first present an autoregressive process for employment in order to find out how well information on the past behaviour of employment helps to predict future values of this series. Afterwards we will add our constructed employment indicator (EMPLINDIC1) to this AR-process for the reference series and test whether our indicator has any value-added with respect to predicting the cyclical pattern of total employment. An autoregressive process for the (normalised) cyclical component of employment can be written as:

\[ y_t = C + \gamma y_{t-i} + \delta y_{t-(1+i)} \]  

(1)

where \( y \) equals NEMPLC. Note that we opted for an AR-process with 2 lags because for our research purposes information on turning points is very important. Furthermore, in order to make the analysis realistic, we should choose \( i \) equal to the publication lag of the reference series. As mentioned before, the R.S.Z. publishes figures on total employment in Belgium with 12 months delay, hence \( i=12 \) in our application.

Estimating equation (1) for the period 93:01-97:01 results in the following estimates for the adjustment speed coefficients: \( \hat{\gamma} = 2.173 \) and \( \hat{\delta} = -2.243 \). Future values of employment can then be forecasted\(^{28}\) as follows (\( y \) equals NEMPLC):

\[ \hat{y}_t = \hat{C} + \hat{\gamma} y_{t-i} + \hat{\delta} y_{t-(1+i)} \]  

(2)

Let us name this series EMPLAR and compare its predictive performance with EMPLINDIC1. Table A2 (see appendix) shows that EMPLAR has a slightly higher correlation coefficient with NEMPLC and from table 3 below (compared

\(^{28}\) Note that the statistical properties of the estimated AR-process do not allow to make accurate forecasts for very long periods ahead. A possible explanation for this is that the process had to be estimated based on a relatively small number of observations due to data limitations on the reference series.
to table 1), we can notice that the test statistics as well as the regression results indicate more accurate forecasts. Panel 7 in figure A4, however, visualises that EMPLAR is not able to predict the timing of the turning points very well. This is not surprising because EMPLAR is only based on information from the past behaviour of employment and cycles are not always of the same length.

**TABLE 3**

*Results measuring the accuracy of forecasting NEMPLC*

<table>
<thead>
<tr>
<th></th>
<th>Test statistics</th>
<th>Regression results</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>MSE</td>
<td>RMSE</td>
</tr>
<tr>
<td>EMPLAR</td>
<td>0.229</td>
<td>0.073</td>
<td>0.270</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMPLINDIC3</td>
<td>0.161</td>
<td>0.035</td>
<td>0.187</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We will now test whether these results can be improved by adding our constructed employment indicator (EMPLINDIC1) to EMPLAR. Aggregation with equal weights\(^{29}\) gives the following specification:

\[
\text{EMPLINDIC3} = (\text{EMPLAR} + \text{EMPLINDIC1}) / 2
\]

This specification does not only increase the correlation with NEMPLC (0.961, see table A2), but it also leads to a further reduction in the forecasting errors (see table 3). And even more importantly, the addition of EMPLINDIC1 results in much better predictions of the exact timing of the turning points (see panel 8 in figure A4). Figure 2 illustrates how the employment indicator (EMPLINDIC1), constructed on the basis of NWHITEC(-2) and iNFAILC(-10), can be improved by adding an AR-process (resulting in EMPLINDIC3) in order to predict the reference series (NEMPLC).

\(^{29}\) Calculating weights via principal component analysis or an OLS-regression (results not shown here) did not alter the outcome because in both cases EMPLAR and EMPLINDIC1 were assigned (approximately) equal weights.
As a conclusion we can say that information on the past behaviour of total employment (captured by the AR-process) seems to be very useful in predicting the general cyclical pattern of the reference series, while current data on interim employment and business failures (combined in EMPLINDIC1) has a value-added because it gives more accurate information on the timing of the turning points and the exact length of the cycles. Note however that because official data on total Belgian employment is published with a delay of 12 months, the AR-process specified above can not play a role as a leading indicator, while EMPLINDIC1 can predict the reference series up to 14 months ahead. Our constructed leading indicator thus has a value-added for labour market analysts and policy-makers.
3. Conclusion

This paper focused on the construction of a leading indicator for the Belgian labour market. The aim was to use only labour market variables in order to predict the cyclical pattern as well as the turning points in total employment. All selected series were adjusted for seasonal and irregular components via the Census X-11 procedure and the Hodrick-Prescott method was used for detrending. Afterwards the cyclical component was derived for each series and these cyclical components were then aggregated into a composite leading indicator. Several criteria, such as small errors to forecast the reference series and accurate predictions of the turning points, were used in order to select a specification for the employment indicator. This resulted in a leading indicator constructed on the basis of white-collar interim work and the number of business failures. It was shown that this indicator resembled quite well the cyclical pattern of observed employment in Belgium and given the fact that official employment figures are published with at least 12 months delay, the indicator could predict employment 14 months ahead. Secondly, it was found that our constructed employment indicator did not perform significantly better when product market variables were added to the specification (i.e. the forecasting errors became slightly smaller, but the prediction of turning points got worse). Furthermore, the predictive performance of our employment indicator was unambiguously superior to all existing leading indicators for the product market. Nevertheless, our employment indicator could be improved by incorporating information on the past behaviour of the reference series (captured by an autoregressive process with 2 lags). The autoregressive process for employment seemed to be very useful in predicting the general cyclical pattern of the reference series, while current data on interim employment and business failures -combined in an employment indicator- supplied more accurate information on the timing of the turning points. Note however that given the serious data problems for the reference series, the autoregressive specification loses its leading character.
References


KB (1997), “De Synthetische KB-Conjunctuurindicator herzien”, *KB Weekberichten*, n°9, 7 maart 1997


OECD (1987), “OECD Leading Indicators and Business Cycles in Member Countries 1960-1985”, *Main Economic Indicators*, Sources and Methods, n°39 (Chapter 8: Composite Indices)

Appendix : Tables and figures

TABLE A1

Description of the variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHITE</td>
<td>total hours worked during 1 month by white-collar interim workers (&quot;bedienden&quot;)</td>
<td>UPEDI</td>
<td>92.1-97.9</td>
</tr>
<tr>
<td>BLUE</td>
<td>total hours worked during 1 month by blue-collar interim workers (&quot;arbeiders&quot;)</td>
<td>UPEDI</td>
<td>92.1-97.9</td>
</tr>
<tr>
<td>TOT</td>
<td>total hours worked during 1 month by white and blue-collar interim workers</td>
<td>UPEDI</td>
<td>92.1-97.9</td>
</tr>
<tr>
<td>VAC1</td>
<td>cumulated number (over 12 months) of unfilled vacancies (excl special programmes)</td>
<td>RVA</td>
<td>89.1-97.6</td>
</tr>
<tr>
<td>VAC2</td>
<td>number of vacancies published in the Flemish newspapers during a month</td>
<td>De Standaard</td>
<td>92.1-97.6</td>
</tr>
<tr>
<td>FAIL</td>
<td>number of business failures during a month (only companies)</td>
<td>Grooteden</td>
<td>89.1-97.9</td>
</tr>
<tr>
<td>DISINC</td>
<td>number of disincorporations during a month (only companies)</td>
<td>Grooteden</td>
<td>89.1-97.9</td>
</tr>
<tr>
<td>START</td>
<td>number of starting businesses during a month (only companies)</td>
<td>Grooteden</td>
<td>89.1-97.9</td>
</tr>
<tr>
<td>IP</td>
<td>industrial production (index numbers)</td>
<td>NIS</td>
<td>89.1-97.5</td>
</tr>
<tr>
<td>SALES</td>
<td>sales industrial firms deflated by the index number of industrial production prices</td>
<td>NIS</td>
<td>89.1-97.4</td>
</tr>
<tr>
<td>EMFL</td>
<td>number of employees in the private sector (at end of each quarter)</td>
<td>E.S.Z.</td>
<td>93Q1-97Q1</td>
</tr>
</tbody>
</table>

TABLE A2

Correlation coefficients between NEMPLC and normalised indicators at the optimal lags or leads.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>leads(+)</th>
<th>lags(-)</th>
<th>correlat coeff.</th>
<th>Indicator</th>
<th>leads(+)</th>
<th>lags(-)</th>
<th>correlat coeff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>NWHITEC</td>
<td>-2</td>
<td></td>
<td>0.822</td>
<td>NKBINDIC</td>
<td>-6</td>
<td></td>
<td>0.803</td>
</tr>
<tr>
<td>NBLUEC</td>
<td>-9</td>
<td></td>
<td>0.805</td>
<td>NINDIC1</td>
<td>-10</td>
<td></td>
<td>0.595</td>
</tr>
<tr>
<td>NHTOTC</td>
<td>-8</td>
<td></td>
<td>0.763</td>
<td>NINDIC2</td>
<td>-10</td>
<td></td>
<td>0.557</td>
</tr>
<tr>
<td>NVAC1C</td>
<td>-6</td>
<td></td>
<td>0.542</td>
<td>NPREDEMP</td>
<td>-8</td>
<td></td>
<td>0.543</td>
</tr>
<tr>
<td>NVAC2C</td>
<td>-3</td>
<td></td>
<td>0.871</td>
<td>EMPLINDIC1</td>
<td>0</td>
<td></td>
<td>0.873</td>
</tr>
<tr>
<td>NFAILC</td>
<td>-10</td>
<td></td>
<td>-0.847</td>
<td>EMPLINDIC2</td>
<td>0</td>
<td></td>
<td>0.898</td>
</tr>
<tr>
<td>NDISINC1C</td>
<td>+7</td>
<td></td>
<td>0.558</td>
<td>EMPLAR</td>
<td>0</td>
<td></td>
<td>0.912</td>
</tr>
<tr>
<td>NSTARTC</td>
<td>+4</td>
<td></td>
<td>0.527</td>
<td>EMPLINDIC3</td>
<td>0</td>
<td></td>
<td>0.961</td>
</tr>
<tr>
<td>NIPC</td>
<td>-6</td>
<td></td>
<td>0.539</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NSALESRC</td>
<td>-9</td>
<td></td>
<td>0.772</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
FIGURE A1

Estimated decomposition of TOT into several components

TOT

Seasonal components TOT

Irregular components TOT

Trend-cycle components TOT

FIGURE A2

Estimated trend of TOT for $\lambda=14400$ (TOTT), $\lambda=1000000$ (TOTT2), $\lambda=100$ (TOTT3)
FIGURE A3

Cyclical components of TOT for different values of $\lambda$

FIGURE A4

Actual (NEMPLC) versus fitted values of several indicators